A Fuzzy Multi-Criteria Decision-Making Framework for Sustainable Truck Selection

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***Abstract* — This study presents a tailored fuzzy multi-criteria decision-making (FMCDM) framework, integrating Fuzzy Decision-Making Trial and Evaluation Laboratory (F-DEMATEL), Fuzzy Analytic Hierarchy Process (F-AHP), and Fuzzy Technique for Order Preference by Similarity to Ideal Solution (F-TOPSIS) for optimized truck selection under uncertainty. While these methods are established in MCDM, their customized integration for fleet selection, incorporating both conventional and electric trucks, enhances practical decision-making. Applied to a Swiss transportation company, the framework systematically captures criteria interdependencies, assigns dynamic weights, and ranks alternatives based on operational, financial, and environmental factors. The results identify efficiency, truck capacity, and fuel consumption as key drivers. This structured approach provides a scalable, data-driven tool for logistics operators, supporting sustainable and cost-effective fleet transitions.**

***Keywords*- Transportation logistics, Electric vehicles, FMCDM, DEMATEL, AHP, TOPSIS.**

I. Introduction

The urgency to transition toward sustainable transport systems has become a focal point in addressing the escalating challenges of climate change. The freight transport sector, particularly road freight, plays a significant role in contributing to greenhouse gas emissions and environmental degradation. Trucks, essential for moving goods across urban and rural areas, also emit pollutants that harm air quality and public health, especially in densely populated regions [1]. With the rapid rise in e-commerce and the growing demand for transportation services, the sector faces mounting pressure to adopt environmentally friendly solutions to mitigate its impact.

Electric trucks have emerged as a viable alternative to traditional internal combustion engine vehicles, offering potential reductions in emissions and noise pollution. However, despite the environmental advantages, their adoption has been slow due to several technical and operational barriers [2]. Selecting the right freight vehicle has therefore become a complex decision-making problem, influenced by multiple criteria ranging from cost and efficiency to environmental impact and operational constraints. The market for trucks is also evolving rapidly, with new technologies and brands entering the scene, creating a dynamic landscape that makes informed decision-making even more challenging. Given this complexity, there is a growing need for robust evaluation frameworks that can help stakeholders compare conventional and electric trucks based on a holistic set of criteria.

This paper proposes a novel fuzzy multi-criteria decision-making (FMCDM) framework that incorporates expert input and addresses uncertainties inherent in the evaluation process. By integrating fuzzy methodologies, this approach allows for the systematic comparison of truck alternatives, balancing qualitative and quantitative factors. The key contributions of this study include: (i) the integration of F-DEMATEL, F-AHP, and F-TOPSIS in a unified framework tailored for truck selection under uncertainty; (ii) the inclusion of both conventional and electric trucks to reflect real-world operational trade-offs; and (iii) the application of the framework in a practical case involving a Swiss transportation company, with transparency in intermediate results The framework provides logistics companies and decision-makers with a practical tool to identify the most suitable vehicle for their operational needs, facilitating a smoother transition toward sustainable freight transport systems.

In the specific context of the Swiss transportation company, vehicle selection is critical, as it directly impacts journey costs and overall operational efficiency. With a wide range of criteria influencing vehicle purchases, including cost, equipment, and environmental considerations, the decision-making process becomes increasingly complex. This study aims to address the question: "How can multi-criteria decision support be used to select the best heavy-duty vehicle, considering diverse purchasing criteria?" Through a structured and systematic approach, the study provides a decision support framework that helps overcome these challenges while promoting sustainable transport solutions.

II. Literature review

In recent years, MCDM frameworks have gained traction as effective tools for addressing complex decisions under uncertainty. For instance, [3] proposed a hybrid AHP-TOPSIS model to select IoT devices in reverse logistics for clinical trials, while [4] combined AHP and F-AHP, and TOPSIS, effectively fir sustainable partners selection, capturing evolving weights across economic, environmental, and social dimensionsThese studies highlight the usefulness of hybrid AHP-TOPSIS methods for structured sustainability decisions in uncertain contexts.

Similarly, the integration of fuzzy logic into traditional MCDM approaches has explanded applicability to subjective inputs. [5] applied the the Balanced Scorecard (BSC) with F-AHP and F-TOPSIS in banking, and [6] used F-AHP-TOPSIS for collaborative software selection, emphasizing group decision-making under ambiguity. Together, they validate FMCDM’s relevance in addressing both qualitative and quantitative data.

Truck selection in logistics operations has emerged as a critical focus area due to the dual imperatives of enhancing operational efficiency and aligning with sustainability objectives. [7] laid the groundwork using fuzzy DEMATEL and hierarchical F-TOPSIS to identify causal links and rank truck options however, they excluded electric vehicles and relied heavily on subjective judgments.

Subsequent studies extended the scope of truck selection methodologies by applying fuzzy-based decision frameworks to specialized contexts, such as refrigerated vehicles [8] and pallet-handling equipment [9]. However, these focused on small-scale or sector-specific applications and offered limited adaptability to dynamic fleet evaluations or electric models. Other research focused on sustainability goals by evaluating drivetrain technologies based on greenhouse gas emissions and energy use [10] or by comparing electric and diesel trucks using total cost of ownership metrics [11]. Nonetheless, such studies often overlooked operational realities, reducing their effectiveness for practical fleet decision-making.

The operational barriers to electric truck adoption such as limited range, high investment costs, and dependence on renewable energy emerging as significant obstacles, are well documented. While [7] focused primarily on conventional trucks, they lacked consideration of contextual factors like energy mix and logistical strategies. A holistic perspective in truck selection that integrates both technological capabilities and operational constraints is required [8]. [2] identified four main barriers for logistics companies transitioning to electrified freight transport systems: practical and technological challenges (e.g., limited vehicle range and inadequate charging infrastructure), financial constraints (e.g., high investment costs and uncertain operational savings), institutional obstacles (e.g., misaligned priorities between actors in the logistics chain), and cultural resistance within organizations, the latter referring to hesitation rooted in brand loyalty or unfamiliar maintenance practices. Challenges such as limited driving range, insufficient charging infrastructure, high initial investment costs, and prolonged charging times continue to hinder widespread implementation [12]. These obstacles are compounded by the need for freight operators to maintain cost efficiency and high logistics performance, which includes reliability, speed, and responsiveness. For companies operating in competitive markets, these considerations are critical, and the uncertainty surrounding electric vehicle performance often leads to hesitation in transitioning to greener alternatives [8].

Specialized contexts, such as mining and construction operations, have also been investigated. [13] employed FMCDM methods, including fuzzy LMAW and MARCOS, to evaluate military dump trucks. Similarly, [14] focused on truck purchasing in construction, using AHP to define criteria weights and Fuzzy Weighted Sum Model to evaluate six truck alternatives. These studies demonstrate FMCDM's methodological flexibility but are limited in addressing sustainability logistics contexts.

Although these studies collectively contribute valuable insights, they reveal significant gaps in the literature. Existing approaches often fail to integrate environmental, economic, and operational factors in a cohesive framework or to address the specific challenges posed by the adoption of electric trucks. Our research seeks to address this gap by proposing a comprehensive FMCDM methodology that evaluates and ranks truck alternatives under uncertainty, integrating expert judgment with sustainability criteria.

III. METHODOLOGY PROPOSED

This study utilizes a hybrid FMCDM framework to evaluate and rank alternatives under uncertainty. The methodology integrates Fuzzy DEMATEL, F-AHP, and F-TOPSIS in a sequential process to ensure comprehensive and robust decision-making (Figure 1). This approach combines the strengths of these methods to handle interdependencies among criteria, assign relative importance to criteria, and rank alternatives effectively.

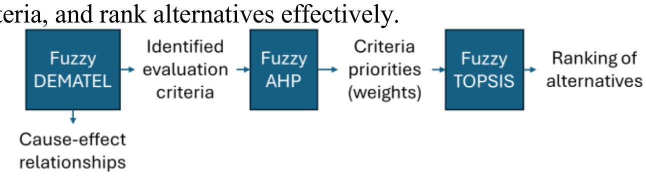

Figure 1. FMCDM Framework for e-truck evaluation

First, fuzzy DEMATEL is applied to identify the interrelationships among the evaluation criteria. The expert and the decision-maker use linguistic terms (e.g., "low," "medium," "high") to evaluate the influence between each criterion. These linguistic evaluations are mapped to triangular fuzzy numbers (TFNs) to handle subjectivity and uncertainty. The commonly used scale is shown in Table 1. The linguistic terms are converted into fuzzy numbers to address uncertainty in the evaluations. A cause-effect analysis is conducted, categorizing criteria into "cause" and "effect" groups.

Table 1 Linguistic Terms and Corresponding TFNs

Linguistic Term	**Triangular Fuzzy Number (l; m; u)**
No influence	(0.0, 0.0, 0.25)
Very low influence	(0.0, 0.25, 0.5)
Low influence	(0.25, 0.5, 0.75)
Medium influence	(0.5, 0.75, 1.0)
High influence	(0.75, 1.0, 1.25)
Very high influence	(1.0, 1.25, 1.5)
Extremely high	(1.25, 1.5, 1.75)

This step highlights the most influential criteria driving the decision-making process, providing a foundation for subsequent analysis. The steps are as follows:

1. Identifying Evaluation Criteria: Criteria are identified through a comprehensive literature review and consultation with experts using a structured questionnaire. Experts evaluate the importance and interdependence of criteria using linguistic terms, which are converted into fuzzy triangular numbers.
2. Construct the Direct Relation Matrix: Experts provide pairwise evaluations of the influence between criteria using linguistic terms, which are converted into fuzzy numbers $\tilde{z}_{ij} = (l_{ij}, m_{ij}, u_{ij})$, where $\tilde{z}_{ij}$ represents a triangular fuzzy number for the pairwise evaluation of criterion i compared to criterion

j; l_{ij} is the lower bound of the fuzzy number, indicating the minimum influence; m_{ij} is the middle value, representing the most likely or expected influence; and u_{ij} is the upper bound, indicating the maximum possible influence.

3. Normalize the Matrix: to obtain $\tilde{x}_{ij}$ which is the normalized fuzzy value derived from $\tilde{z}_{ij}$. Normalization ensures that the values are scaled relative to the largest sum of influences.

$$\tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{\max(\sum_{j=1}^{n} u_{ij},\ \sum_{i=1}^{n} u_{ij})}$$

4. Calculate the Total Relation Matrix:

$$\tilde{T} = \tilde{X} \cdot (I - \tilde{X})^{-1}$$

Where $\tilde{T}$ represents the relation matrix, which captures the total influences (direct and indirect) between criteria after applying the fuzzy DEMATEL process; and $\tilde{X}$ is the normalized direct-relation matrix, with elements $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ and I is the identity matrix.

5. Determine Cause and Effect: Compute the sums of rows (D) and columns (R), where D+R is the importance, and D-R is the influence. Criteria with $D - R > 0$ are "causes," while those with $D - R < 0$ are "effects."

Next, F-AHP is used to determine the relative importance of the criteria identified in the fuzzy DEMATEL step. Experts perform pairwise comparisons of criteria using fuzzy linguistic terms, capturing subjective judgments and uncertainty. These comparisons are synthesized into fuzzy numbers, which are then defuzzified to compute weights for each criterion. The resulting weights reflect the criteria's relative significance and serve as inputs for the ranking stage. The steps include:

1. Fuzzy Pairwise Comparison Matrix: Experts perform pairwise comparisons of criteria using linguistic terms, converted into triangular fuzzy numbers. A comparison matrix $\tilde{A} = \{\tilde{a}_{ij}\}$ is constructed, where each element $\tilde{a}_{ij}$ represents the relative importance of criterion *i* over criterion *j*.
2. Weight Derivation: A standard fuzzy extent analysis approach is used to calculate the criteria weights, ensuring consistency in pairwise comparisons.
3. Defuzzification: The fuzzy weights are defuzzified using the centroid method:

$$W_i = \frac{l_i + m_i + u_i}{3}$$

The defuzzified weights, representing the relative importance of each criterion, are first normalized to ensure their total sums to 1. This normalization process provides the relative weight of each criterion in crisp form, which is essential for subsequent decision-making steps. These normalized weights are then interpreted to reflect the significance of each criterion and are directly applied in the evaluation of alternatives.

Finally, F-TOPSIS is employed to rank the alternatives based on their performance against the criteria. As part of the F-TOPSIS process, each evaluation criterion is categorized as either benefit-based or cost-based. Benefit-based criteria, such as truck capacity, efficiency, cab comfort, and safety features, are those where higher values are preferable. Cost-based criteria, such as fuel consumption, initial investment cost, and gas emissions, are those where lower values are preferred. This distinction is critical for normalization, as it ensures that the performance of each alternative is assessed relative to the correct objective: maximizing desirable attributes while minimizing undesirable ones. Then, a decision matrix is constructed, where alternatives are evaluated against criteria using fuzzy scores. Each alternative is compared to a fuzzy ideal solution (representing the best possible performance) and a fuzzy anti-ideal solution (representing the worst performance). The alternatives are then ranked based on their relative closeness to the ideal solution, with higher scores indicating better alignment with the desired criteria. The steps include:

1. Fuzzy Decision Matrix: Alternatives are evaluated against criteria using linguistic terms (e.g., "Good," "Poor"), converted into triangular fuzzy numbers $\tilde{v}_{ij}$.
2. Normalization: The fuzzy decision matrix is normalized:

$$\tilde{r}_{ij} = \begin{cases} \dfrac{v_{ij}}{\max v_{ij}}, & \textit{if criterion is benefit based} \\ \dfrac{\min v_{ij}}{v_{ij}}, & \textit{if criterion is cost based} \end{cases}$$

3. Weighted Normalized Decision Matrix ($\tilde{V}_{ij}$): The normalized values are multiplied by the defuzzified weights:

$$\tilde{V}_{ij} = \tilde{r}_{ij} \cdot W_i$$

4. Calculate the Positive (A^*) and Negative (A^-) Ideal Solutions:

$$A^* = \{\max \tilde{v}_{ij}\}, \qquad A^- = \{\min \tilde{v}_{ij}\}$$

5. Calculate the relative closeness to the ideal solution:

$$C_i^* = \frac{\sqrt{\sum_{j=1}^{n} (\tilde{v}_{ij} - A_j^-)^2}}{\sqrt{\sum_{j=1}^{n} (\tilde{v}_{ij} - A_j^*)^2} + \sqrt{\sum_{j=1}^{n} (\tilde{v}_{ij} - A_j^-)^2}}$$

The alternative solutions are then ranked in descending order of C_i^*, with higher values indicating better performance. This methodology is particularly suitable for addressing uncertainty and complexity in decision-making scenarios, such as evaluating and transitioning from conventional to electric trucks. It leverages expert opinions to handle scenarios where quantitative data may be incomplete or incomparable, ensuring robust and reliable outcomes.

IV. Implementation Case

The Swiss transportation company, in which the methodology was implemented, operates an extensive network, offering road, rail, maritime, and air transport services, alongside contractual logistics and storage solutions at 68 sites within Switzerland and 9 abroad. Notably, the company integrates sustainability into its operations, with 60% of its transport conducted via rail—a feature that significantly reduces CO2 emissions. In 2022, the company expanded its sustainability efforts by acquiring 13 electric vehicles for city and suburban deliveries, reflecting its commitment to minimizing environmental impact. To further optimize its fleet, an interview was conducted with the Deputy Head of Geneva Disposition, to define objectives, vehicle alternatives, and key purchase criteria. Moreover, quote requests were also sent to various truck providers to obtain detailed information on alternatives and contractual terms.

The company’s criteria for truck selection, influenced by previous studies on heavy-duty vehicle purchasing [7], [14], were finalized in collaboration with the company. These criteria span operational, financial, and environmental considerations:

1. Fuel consumption (C1): Evaluates the fuel required per distance based on varying loads and environments (urban, regional, long-distance).
2. Truck operating time (C2): Considers continuous operation capabilities, factoring in driver shifts and electric vehicle charging times.
3. Initial investment cost (C3): Accounts for the chassis, structure, and upfront purchase costs.
4. Depreciation (C4): Includes purchase price, expected lifespan, and reinvestment needs.
5. Gas emissions (C5): Relates to compliance with EURO standards and pollutant levels.
6. Cab comfort and ergonomics (C6): Prioritizes driver well-being, including practical controls and optimal visibility.
7. Efficiency (C7): Measures engine performance and utility of the truck's structure.
8. Truck capacity (C8): Considers payload, total weight, and axle configuration.
9. Ease of resale (C9): Evaluates the long-term market value and resale potential of the vehicle.
10. Consumable parts cost (C10): Covers expenses for replaceable components like tires and fluids, often included in maintenance contracts.
11. Safety tools for accidents (C11): Includes advanced safety features like braking assistance, driver aids, and backup cameras.

While some criteria are quantitative (e.g., fuel consumption), others, such as cab comfort and ease of resale, involve value judgments and are inherently qualitative. Fuzzy methodologies are employed to handle the uncertainty and subjectivity of these evaluations [15]. For example, the initial investment cost criterion (C3) incorporates not only the truck's base price but also the cost of its structure.

While diesel trucks are preferred, the company is also willing to consider additional electric vehicles but does not currently explore hybrid, hydrogen, or biogas options. Several requests for quotes were submitted, and each provider proposed vehicles tailored to The company’s needs, including trucks with liftgate-equipped bodies suitable for event transportation. This structured and collaborative approach ensures a comprehensive evaluation of truck alternatives (A), integrating the company’s operational priorities with sustainable transport goals. The alternative trucks under consideration for purchase are:

1. Iveco S-Way – Diesel (A1)
2. Scania P320 B4x2 NB – Diesel (A2)
3. Scania Regional BEV – Electric (A3)
4. Volvo FL 280 4x2R – Diesel (A4)
5. Designwerk MID CAB 4x2R – Electric (A5)

V. Results and Discussion

A. Fuzzy DEMATEL Results

The D-R values in Table 2 classify criteria into cause and effect categories. Cause criteria, with positive D-R values, influence other factors and play a central role in decision-making. Among these, truck operating time (C2) has the highest influence (D-R = 3.00), as frequent use leads to increased fuel consumption (C1), more frequent part replacements (C10), and higher gas emissions (C5). Other significant cause factors include truck capacity (C8), which affects ease of resale (C9), price (C3), and efficiency (C7). Similarly, cab comfort and ergonomics (C6) impact truck operating time (C2) and initial investment cost (C3), while fuel consumption (C1), initial investment cost (C3), and efficiency (C7) also play a crucial role in shaping operational and financial performance.

Table 2 Swiss Transport Company Case: Final Values

No.	R	D	D+R	D-R	Cause or Effect?
C1	2.88	3.63	6.51	0.75	Cause
C2	1.00	4.00	5.00	3.00	Cause
C3	3.97	4.16	8.13	0.19	Cause
C4	4.02	1.22	5.24	-2.79	Effect
C5	3.17	3.12	6.29	-0.05	Effect
C6	2.23	3.58	5.82	1.35	Cause
C7	3.33	3.47	6.79	0.14	Cause
C8	2.39	4.00	6.38	1.61	Cause
C9	4.70	1.30	5.99	-3.40	Effect
C10	3.08	2.71	5.79	-0.37	Effect
C11	2.68	2.26	4.94	-0.41	Effect

Effect criteria, with negative D-R values, are shaped by the cause factors rather than influencing the system. The most affected ones include ease of resale (C9), which depends on investment cost (C3), truck capacity (C8), and efficiency (C7). Depreciation (C4) is similarly influenced by initial costs and usage patterns. Gas emissions (C5), consumable parts cost (C10), and safety tools for accidents (C11) are also indirectly shaped by fuel consumption, operating time, and truck specifications.

The D+R values in Table 2 indicate the overall importance of each criterion within the decision-making process. Initial investment cost (C3) is the most significant (D+R = 8.13), as it directly affects both operational costs and resale value. Efficiency (C7), fuel consumption (C1), truck capacity (C8), and gas emissions (C5) also rank highly in importance, playing a crucial role in optimizing truck performance and long-term cost-effectiveness. By identifying and prioritizing these relationships, the AHP process can effectively assign weights to the most influential criteria, ensuring that TOPSIS ranks alternatives based on factors that drive overall truck selection and operational efficiency.

B. F-AHP and F-TOPSIS Results

To evaluate the interrelation between criteria, the F-AHP method was applied. The company provided input to complete the fuzzy judgment matrix, determining the relative importance of each criterion. The fuzzy synthetic extent values were derived by summing the geometric means, computing their inverse, and multiplying the results by the original values. These normalized values, which indicate the relative importance of each criterion, are presented in Table 3. Each value is expressed as a triangular fuzzy number (TFN) in the format (l; m; u), where l (lower bound) represents a conservative estimate, m (middle value) is the most likely or expected importance, and u (upper bound) reflects an optimistic scenario. This approach accounts for variations in expert judgment, ensuring robustness in the weighting process.

Table 3 Fuzzy Synthetic Extent Values

Criterion	Fuzzy Synthetic Extent (l; m; u)
C1	(0.095; 0.098; 0.101)
C2	(0.085; 0.089; 0.092)
C3	(0.094; 0.097; 0.1)
C4	(0.086; 0.088; 0.09)
C5	(0.081; 0.084; 0.088)
C6	(0.075; 0.078; 0.082)
C7	(0.097; 0.1; 0.103)
C8	(0.096; 0.099; 0.103)
C9	(0.084; 0.087; 0.091)
C10	(0.093; 0.096; 0.099)
C11	(0.081; 0.083; 0.086)

The results indicated that efficiency (C7) (0.103) and truck capacity (C8) (0.103) had the highest synthetic extent values, confirming their significance in the decision-making process. Fuel consumption (C1) (0.101) and initial investment cost (C3) (0.1) followed closely, reinforcing the importance of operational cost and financial viability. Consumable parts cost (C10) (0.099) had moderate importance, while criteria such as truck operating time (C2), depreciation (C4), gas emissions (C5), cab comfort (C6), ease of resale (C9), and safety tools (C11) had the lowest values, indicating minimal influence on the decision.

For the F-TOPSIS analysis, alternatives were assessed based on the selected criteria. The decision matrix was normalized and weighted according to the F-AHP results, eliminating criteria with low significance. The ideal positive and negative solutions were identified, and distances from these solutions were computed to establish a ranking. Table 4 shows selected intermediate results from the F-TOPSIS procedure, including distances from ideal and anti-ideal solutions and the resulting proximity coefficients used to rank the truck alternatives.

Table 4 F-TOPSIS Intermediate Results

Alternative	D^+	D^-	C_i*
A1	0.07	0.36	0.84
A2	0.21	0.31	0.60
A3	0.17	0.24	0.59
A4	0.23	0.23	0.50
A5	0.34	0.18	0.34

The final ranking placed Scania (A2) at the top with a proximity coefficient of 0.836, making it the best choice. It was followed by Iveco (A1) (0.596) and Volvo (A4) (0.589). The Scania (A3) (0.500) and Designwerk (A5) (0.343) ranked lowest, primarily due to their limited battery efficiency and high costs. Although the company historically favored Volvo, the results showed that Scania's diesel truck emerged as the optimal choice due to its balance of efficiency, fuel consumption, and cost. The electric models, despite their environmental benefits, were disadvantaged by their limited range and high purchase price, making them less viable options for the company at this time.

C. Discussion of results

The combination of Fuzzy DEMATEL, F-AHP, and F-TOPSIS provided a structured approach for evaluating truck selection criteria and ranking alternatives. Fuzzy DEMATEL identified efficiency (C7), truck capacity (C8), and fuel consumption (C1) as the most influential factors, meaning they drive decision-making. Initial investment cost (C3) also emerged as a critical driver with the highest overall importance score (D+R = 8.13). This reflects its dual influence on operational costs and long-term financial performance, underscoring its central role in shaping purchasing decisions. In contrast, ease of resale (C9) and depreciation (C4) were dependent on other factors rather than influencing the decision directly. This analysis helped refine the selection of criteria for F-AHP by confirming the most relevant factors in the decision-making process. F-AHP reinforced these findings, showing that efficiency and truck capacity were the most important criteria, followed by fuel consumption and initial investment cost. This confirmed the priority of optimizing performance and cost-effectiveness. Criteria such as gas emissions, ease of resale, and cab comfort were considered insignificant, as they did not significantly impact overall truck selection.

F-TOPSIS applied these weighted criteria to rank the available alternatives. The results confirmed that Scania diesel truck (A2) ranked as the best choice with a proximity coefficient of 0.836, making it the preferred option for purchase. It was followed by the Iveco diesel truck (A1) (0.596) and the Volvo diesel truck (A4) (0.589), which ranked closely behind. The Scania electric model (A3) (0.500) and Designwerk (A5) (electric) (0.343) placed last, mainly due to limited battery efficiency and high costs.

Currently, 80% of the company's fleet consists of Volvo trucks, and a preference for this brand was initially expressed. However, the results indicate that Scania's diesel model (A2) is the best option, even if switching from Volvo would require an operational adjustment. The Iveco S-Way (A1) was considered a viable alternative but was noted to have high fuel consumption (34.1 L/100 km) despite its large fuel tank, offering only 11% more autonomy (approximately 158 km) compared to the Scania (A2). The Volvo (A4), initially favored, ranked third because it did not excel in efficiency, which was the most important criterion. Its 280 HP engine was less powerful, and its range was lower relative to its fuel tank capacity. Additionally, as the only 16-ton vehicle in the comparison, it was not the most suitable option for the company's needs.

The two electric trucks ranked last, primarily due to limited range and high purchase price, nearly three times higher than diesel models. The Scania Regional BEV (A3) performed moderately well, as it was rated good or moderately good across most purchase criteria. However, the company acknowledged that lack of experience with electric vehicles may have influenced the evaluation results. The Designwerk (A5) placed last due to poor battery efficiency, lower payload capacity, and a particularly high price, making it the least suitable option for the company's operational requirements.

VI. CONCLUSION

This study contributes to the literature by developing a tailored FMCDM framework, integrating Fuzzy DEMATEL, F-AHP, and F-TOPSIS to address the complexities of heavy-duty truck selection under uncertainty. While these methodologies have been individually applied in decision-making contexts, their systematic integration for fleet selection, considering both conventional and electric trucks, offers a structured and practically relevant approach for logistics operators navigating sustainability transitions.

The analysis identified efficiency, truck capacity, and fuel consumption as the most influential criteria, confirming their critical role in balancing performance, cost-effectiveness, and reliability. The results demonstrated that Scania diesel truck is the most suitable alternative for the company, despite the company's initial preference for Volvo. Although electric trucks present environmental benefits, they were found to be less practical due to high costs, limited range, and operational uncertainties. The Scania Regional BEV performed moderately well, but its high price and lack of operational familiarity made it a less viable option. The Designwerk MID CAB 4x2R ranked lowest, primarily due to poor battery efficiency, lower payload capacity, and significant investment costs.

By offering a scalable and data-driven decision support framework, this study bridges the gap between theoretical MCDM methodologies and real-world fleet management challenges. The proposed approach enables logistics companies to systematically evaluate truck alternatives, ensuring that economic, operational, and environmental considerations are integrated into strategic fleet decisions. Future research could refine this framework by enhancing its adaptability to evolving logistics needs, integrating stakeholder preference dynamics, and incorporating life-cycle sustainability assessments to account for long-term economic and environmental impacts. Additionally, expanding the approach to include multi-period decision-making and uncertainty modeling for emerging technologies could further improve its applicability in rapidly changing transportation landscapes.

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